Vehicle Classification and Counting for Vehicle Census

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***Abstract*—Vehicle classification has been significantly important to vehicle census as it provides traffic count information to reflect the traffic density of a particular roadway. However, it has been a time consuming and sophisticated task to classify different vehicles into the desired category. Besides, the hardware-based technique used for classification leads to high cost of implementation and maintenance. Thus, we proposed an image processing based solution to extract the features of each vehicle in the traffic scene. The proposed framework incorporates a combination of detection, tracking and classification of vehicle to ensure high accuracy and performance for vehicle census. Experimental results show that our proposed framework can be applicable in real world applications.**

***Index Terms*—Vehicle Census; Vehicle Classification; Image Processing**

I. INTRODUCTION

Recently, traffic vehicle census has shown great significance as the information produced can be useful in different real life applications especially for reducing traffic congestion as well as road planning [1]. In this case, vehicle classification plays a vital role in classifying different types of vehicle and produces a unique counter for each type. Nevertheless, vehicle classification has been a time consuming and sophisticated task in order to generate the traffic statistic for vehicle census. Thus, this study is being carried out to identify the necessary requirements as well as to develop an efficient algorithm for vehicle classification. There are several ways to acquire the information of vehicle type such as hardware-based sensors and software-based approach using image processing technique. However, the hardware-based technique usually is not being considered due to higher implementation and maintenance cost [2]. Therefore, the motivation of the study is clear as automated vehicle classification with the use of computer vision has become more demanding to assist in these problems. The software-based method provides ease of maintenance and visualization capabilities which enables the extraction of richer information with wider view of traffic scenes [3].

The rest of the paper is organized as follows. In Section II, the related works of vehicle classification is highlighted to compare and analyze the existing technique being used. Besides, the proposed methodology is presented in Section III while experiment and result will be covered in Section IV. Section V concludes the paper with some future works to be discussed.

II. RELATED WORKS

There are numerous approaches that have been studied by researchers whereby each technique use different features and procedures in order to detect and classify vehicles. One of the methods that has been referred by most of the research works is the length-based vehicle classification proposed by [4] as it provides the most basic and fundamental concept in vehicle classification. The proposed method makes use of the registration line to detect the presence of vehicles in the scene. A longitudinal line is placed along each line of travel to measure the length of each vehicle while the result is stored in an array to compute mean, standard deviation and range for classification purpose. In this case, the particular array is considered to contain trucks if the range is greater than 75% of the mean vehicle length. The vehicle is classified as truck provided that its length is greater than one standard deviation above the mean. However, this method only focuses on classifying trucks while the result is mainly dependent on the statistic of real data in which the mean and standard deviation obtained can be varied in different scenes.

[5] presented a vehicle classification algorithm using size and shape of vehicle. Grayscale conversion and binary thresholding are being performed on the vehicle image as pre-processing task in this approach. Then, erosion process is carried out on the pre-processed image while the boundary of vehicle is extracted through subtraction of eroded image from the input image. Features vector is derived from the vehicle boundary image and Euclidean distance is used to measure the similarity between the input vectors and template vectors of each vehicle class. Nevertheless, this proposed technique uses image instead of video as an input for classification.

A new technique suggested by [6] categorizes the vehicles based on estimation of direction angle (DA). Vehicle detection is performed on the captured frame sequences based on the widely used background subtraction approach. The operation basically computes the absolute difference between current frame and a reference frame, which is also known as background image [7]. A minimal up-right rectangle is formed around each detected vehicle whereby most of the car objects are square bounded while motorcycles are typically rectangular bounded. Then, the DA to the first primary axis (FPA) within the bound is evaluated as a specific feature to classify vehicles because motorcycles tend to have lower DA values compare to car category. However, the proposed strategy is sensitive to illumination change due to static background image and it only focuses on classifying motorcycles out from the traffic flow.

The usage of bounding box has been one of the most popular techniques in vehicle classification due to its efficiency in recognizing the size of vehicles. [8] proposed an algorithm for detecting, tracking and classifying vehicles from different video sequences with the use of bounding box. A robust approach by using frame differencing method is applied on the consecutive frames to detect moving objects in the scene [9]. Then, opening morphological approach is being adopted whereby erosion is followed by dilation process to remove the noisy region besides magnifying the detected vehicle object to be more obvious for features extraction. A bounding box is being drawn over the detected vehicle object in which the width and height can be utilized to calculate the aspect ratio and extent of vehicle for classification process. The segmented vehicle object is then tracked by employing a region-based tracking method to discover the correspondence of detected vehicles in subsequent frames to prevent multiple counting issues. However, the algorithm does not include any filter process to recognize each detected object as a valid vehicle object. There is no pre-processing task to reduce the computational cost of overall process as well.

III. METHODOLOGY

In this paper, we proposed a simple and efficient algorithm in order to detect, recognize, track and classify vehicle based on geometry features extracted from each vehicle object. Geometry refers to a mathematical field regarding the shape, size and position of an object [10]. Simple dimensional measurement such as height, width, aspect ratio and area are used as features in this geometric classification approach due to their low computational cost. Thus, the assigned class label for vehicles is usually performed based on user-determined range of measurements [11]. The algorithm basically categorize the detected vehicles into size of small, medium and large, which correspond to motorcycle, car and heavy vehicle respectively. Figure 1 shows the block diagram of our proposed framework.

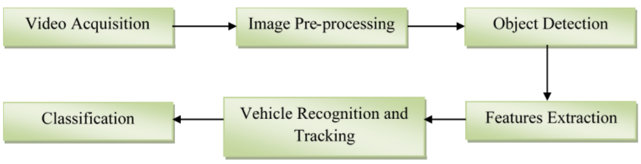

Figure 1: Proposed framework of vehicle classification for vehicle census

A. Video Acquisition

First and foremost, a video camera is being set up to monitor and record the traffic road scene for a particular duration. The camera calibration is then configured based on the technique used by classification using DA to ensure that the measurements of vehicles' size for each class are distinct and easily obtained from the scene [12]. Besides, the camera is mounted at the elevation of 7.85m from the road surface. In this case, the height of the camera position has to be constant as it significantly affects the dimension of the extracted vehicle region. The video sequence acquired from the camera is then extracted into frames at a particular frame rate.

B. Image Pre-processing

According to [5], the images extracted from the video can be described by the combination of three colors namely red, green and blue colors. Grayscale conversion is being performed at this stage to transform the input image from the RGB color space into a grayscale image as color information does not assist in extracting important features in this project. Equation 3.1 illustrates the formula of grayscale conversion. R, G, and B refer to the pixel intensities in red, green and blue component while G_s is the output grayscale image. i and j indicate the coordinates of pixel in the image.

$$G_s(i,j) = 0.299 * R + 0.587 * G + 0.114 * B \quad (1)$$

Besides, the frame extracted in real life condition usually consists of noises. Noise can be defined as the deviation of pixel values from the correct intensity of real scene due to errors in image acquisition [13]. In this case, smoothing is being performed on the grayscale image by using Gaussian blur operation to reduce the noise level in the image. The effect is just like viewing the image through a translucent screen. Equation 2 described the Gaussian function where σ is the standard deviation of the Gaussian distribution. x is the distance from origin in horizontal direction while y is the distance from origin in vertical direction. Figure 2 shows the effect of pre-processing task on captured traffic scene.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \quad (2)$$

Figure 2: Effect of grayscale conversion and Gaussian blur operation

C. Object Detection

Frame differencing approach is performed on two subsequent frames in the video scene. It is a process of subtracting two consecutive frames in a video sequence in order to segment the foreground object without the need of previous background learning [8]. This can be described in Equation 3 where $P1$ and $P2$ are two consecutive frames while Q is the resulting image. i and j refer to the pixel coordinates in the frame.

$$Q(i,j) = P2(i,j) - P1(i,j) \quad (3)$$

Next, binary thresholding takes place in order to transform the resulting image into a binary image. Based on Equation 4, $(x,)$ is the intensity value of a pixel and $(x,)$ is the intensity value of an output pixel. $maxVal$ is a predefined maximum value while $thresh$ is the threshold value. In this project, threshold is set to 20 while any intensity above this value is set to 255 and the remaining one is set to 0 to produce an output image with only black and white intensity.

$$dst(x,y) = \begin{cases} maxVal, & src(x,y) > thresh \\ 0, & otherwise \end{cases} \quad (4)$$

Furthermore, morphological operation is used to modify and enhance the structure of binary image with the help of structuring element. In this case, dilation process allows foreground object to grow in size and connect its relevant parts to each other. Furthermore, erosion process is being used to remove small unwanted object in the background which is not connected to the foreground object. Thus, opening morphological technique is applied whereby erosion is followed by dilation to remove small unwanted object while preserving and increasing the size and shape of vehicle object [14]. The three operations are presented in Equation 5 to 7. Figure 3 reveals the effect of frame differencing, binary thresholding and morphological operation.

$$Dilation = A \oplus B \tag{5}$$

$$Erosion = A \ominus B \tag{6}$$

$$Opening = (A \ominus B) \oplus B \tag{7}$$

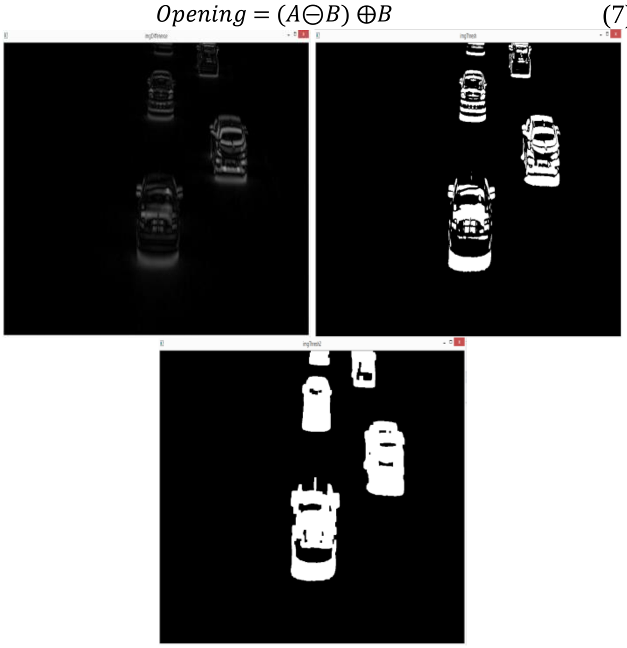

Figure 3: Effect of (a) frame differencing (b) binary thresholding (c) morphological operation

D. *Features Extraction*

Contour can be referred to as the boundary of an object in which a population of pixels separates the object from the background [15]. Contour tracing is performed on the binary image from the previous stage through Theo Pavlidis' algorithm. It basically raster scans the binary image and finds the border of each object. Then, a convex hull is formed by using the coordinates of detected contour through Sklansky's Scan. Convex hull can be defined as the smallest convex polygon which containing a given set of points [16]. The area of the convex polygon then can be used to represent the area of the detected object. Figure 4 shows the effect of contour tracing and convex hull generation.

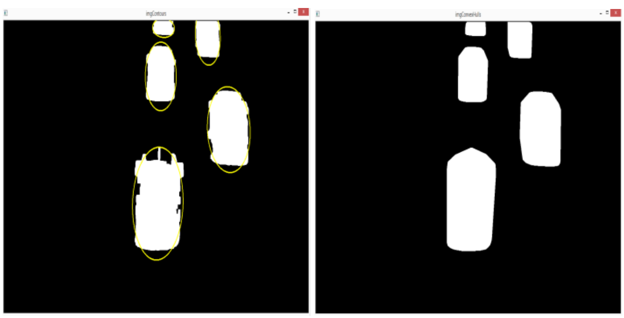

Figure 4: Effect of (a) contour tracing (b) convex hull generation

After that, a bounding box is drawn over each detected object by calculating the minimal up-right bounding rectangle of the convex hull. The rectangle formed can be used to analyze the dimension of the vehicle. In this case, the width and height of the bounding box can be easily extracted and used to compute area and aspect ratio. Based on Figure 5, *x1* refers to the lowest coordinate value in horizontal x-axis while *x2* is the highest coordinate value in the same axis. Similarly, *y1* and *y2* refer to the lowest and highest coordinate values in vertical y-axis.

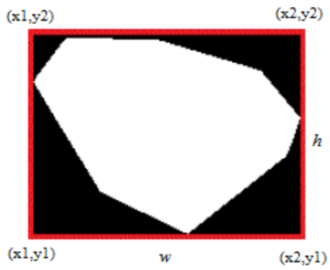

Figure 5: Bounding rectangle formed around convex hull

E. *Vehicle Recognition and Tracking*

Vehicle recognition is important to identify the detected object as vehicle and filter out non-vehicle object before the classification stage. A class is created which acts as the template or blueprint to describe the state and behavior of each vehicle object. Several attributes are stored in the class such as contour, width, height, aspect ratio, area and extent. In this case, each attribute is associated with a condition while the detected object must fulfill all the conditions in order to be recognized as a vehicle. For instance, an object with area that is less than a specific minimum area of vehicle is not qualified to be a vehicle. Each recognized vehicle is being tracked to eliminate the problem of multiple counts on a particular vehicle. The process of tracking basically works to find out the correspondence of detected vehicles at a different timing. Mouse move algorithm is being proposed to predict and estimate the trajectory of each vehicle object based on its center position. The main concept of the algorithm is to discover the next position of an object based on its previous movement with associated weight being applied. Figure 6 shows the example of traffic scene with vehicle tracking capability.

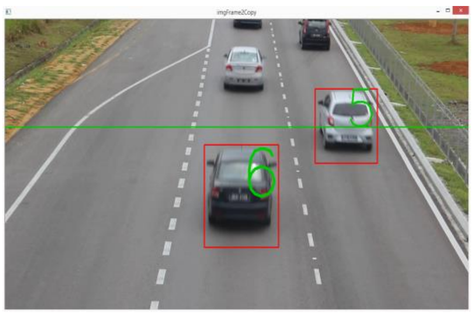

Figure 6: Example of vehicle tracking on traffic scene

F. *Classification*

In the classification stage, a registration line is being set up and drawn in the scene which indicates the position where bounding box is extracted for classification purpose. In this case, a vehicle is considered to be counted and classified if the detected vehicle passed over the line. The input features consist of area of the convex polygon, width and height of the bounding box whereby all of these are extracted from the previous features extraction phase. The aspect ratio (A_R) can be calculated as in Equation 8 where h and w refer to height and width respectively. Then, a range of measurement is being produced to construct the rules for classifying vehicles into small, medium and big category. Table 1 shows the range of measurement for each feature after several experiments are conducted in this project.

$$A_R \frac{h}{w} \tag{8}$$

Table 1
Range of measurement of geometry features

Features	Vehicle		
	Motorcycle	Car	Heavy vehicle
Width	51-100	101-200	201-400
Height	101-180	120-230	231-500
Aspect ratio	1.5-3.0	0.8-1.3	0.9-2.5
Area of convex hull	6000-12000	13000-36000	40000-140000

IV. Experiment and Result

The experiments were carried out to evaluate the efficiency and performance of the proposed methodology. Several traffic scenes are used to conduct the experiments while analysis is then performed in terms of the accuracy of vehicle classification as well as vehicle counting. An 18.0 megapixel digital camera, Canon EOS 600D is being used for capturing the road scene on the bridge which is right in front of the old campus of University Malaysia Sarawak (UNIMAS). The camera is supported by a tripod to stabilize and elevate its required position. The traffic scenes captured are then used to test the performance of the overall system. The prototype is developed in C++ programming language by using Microsoft Visual Studio Community 2015 which is free to download from the official website. In addition, a computer vision library, namely OpenCV (Open Source Computer Vision) is then included in using the software to extend its functionality in computer vision for image processing operation.

Table 2 reveals the error rate of vehicle counting based on the number of vehicles counted and the actual total number of vehicles in the traffic scenes. The result shows that the algorithm shows its robustness by performing efficiently in terms of vehicle counting for the application of vehicle census. The only inaccurate counting issue occurs in video 3 was due to recalculation of vehicle in the situation of vehicle occlusion.

Table 2
Error rate of vehicle counting

Video	Number of Vehicles Counted	Total Number of Vehicles	Error Rate
1	25	25	0.00%
2	28	28	0.00%
3	40	39	0.03%
4	36	36	0.00%

Moreover, Table 3 shows the accuracy of vehicle classification by testing with the captured traffic scenes. It can be shown that the classification algorithm produced very good result by achieving 100% accuracy on the first two traffic scene as well as approximately 93% and 89% on the remaining scenes. In video 3 and 4, misclassification only exists with occlusion situation as more than 1 vehicle is detected in a single bounding box. However, it does not affect the results of vehicle census in this project.

Table 3
Accuracy of vehicle classification

Video	Number of Vehicles Correctly Classified	Total Number of Vehicles	Classification Accuracy
1	25	25	100.00%
2	28	28	100.00%
3	36	39	92.31%
4	32	36	88.89%

V. Conclusion

In conclusion, a simple and efficient algorithm of vehicle classification for vehicle census is produced to classify the vehicle into motorcycle, car and heavy vehicle. The computational cost of overall system is low due to relevant pre-processing while convex hull ensures a standard representation of the area of vehicles that acts as a distinct feature for vehicle classification. Besides, vehicle recognition and tracking process is also taken into consideration to track and filter non-vehicle object compare to other reviewed methods of this study. The experiments indicate that the prototype works well to classify and generate counting information for each vehicle category. As future work, the proposed methodology can be enhanced by handling the situation of vehicle occlusions. Appearance-based features also can be considered to integrate with geometry-based features to optimize the performance of vehicle classification.

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